Betting on bitcoin: a profitable trading between directional and shielding strategies

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Abstract

In this paper, we come up with an original trading strategy on Bitcoins. The methodology we propose is *profit-oriented*, and it is based on buying or selling the so-called *Contracts for Difference,* so that the investor's gain, assessed at a given future time t, is obtained as the difference between the predicted Bitcoin price and an apt threshold. Starting from some empirical findings, and passing through the specification of a suitable theoretical model for the Bitcoin price process, we are able to provide possible investment scenarios, thanks to the use of a Recurrent Neural Network with a *Long Short-Term Memory* for predicting purposes.

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1 Introduction

For last decades, cryptocurrencies have been increasingly playing a leading role in the worldwide economic and financial scenario. Among the various cryptocurrencies currently available to potential buyers, *Bitcoin* (BTC, henceforth) is certainly the most famous and most interesting example. As proof of this, it is sufficient to note that the 2019 BTC market capitalization was equal to about $bn 170, representing the 53% of the leading cryptocurrencies market capitalization.[1]

Focusing on BTC, the literature has highlighted its peculiar structure. In some respects, BTC can be likened to a standard currency, because of its limited intrinsic value. In this perspective, the US dollar seems to represent to best touchstone, even though, by definition, BTC is not issued by any central bank. Meanwhile, BTC shares several interesting properties with some safe-haven assets, such as gold. However, BTC cannot be considered a commodity, due to its inability to perform financial hedging, see e.g., Byström and Kryger (2018) for further details.

There is at least a couple of conceivable reasons why both academics and practitioners are currently participating in such a large development of the cryptocurrencies' phenomenon.

The first motivation is related to their original task. It is worth recalling that the cryptocurrencies were born as an alternative form of payment to the traditional ones, see e.g., Nakamoto (2008) in reference to BTC, which can rightly be considered the most famous issued cryptocurrency. More precisely, they represent a form of digital payment, like the well-known bank transfers or, more generally, online money transfers, such that the presence of intermediaries is not allowed, as in the case of cash payments, see e.g., Ametrano (2016) and references therein.

The second rationale behind the aforementioned success for the family of cryptocurrencies is probably to be found in the ever-growing willingness on the part of financial operators to find new forms of investment that guarantee large profit margins, without taking into suitable account the level of risk associated with these financial transactions. In other words, cryptocurrencies can be considered a new form of speculative investment.

Compared to classical investment products (such as equity indices, or standard currencies), the cryptocurrencies are characterized by a significant volatility level, see e.g., Bucko et al. (2015) and Kyriazis et al. (2019). As a consequence, these kinds of products turn out to be highly palatable for *risk-seeking* investors, while remaining less attractive to *risk-averse* investors. Thanks to the aforementioned remarks about the BTC nature, and taking into account the crucial role played by volatility, recently many authors have started to look at BTC (and, more generally, all the cryptocurrencies traded on the main platforms) as an example of pure risky securities. Roughly speaking, BTC can be used as a *classic* financial tool, on which investors might act in different ways. For example, an agent may directly focus on the security, namely by betting on potential prices' upturns or dips. Alternatively, the same agent can build any

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[1] See https://www.statista.com/statistics/730782/cryptocurrencies-market-capitalization/ for further details.

appropriate investment strategies involving derivative instruments, see e.g., Bistarelli et al. (2019) for an in-depth analysis.

It is worth highlighting that the growing interest in cryptocurrencies is revealing under several aspects. Many authors have been focusing on the study of appropriate trading software systems, trying to identify both their strengths and weaknesses, insisting on the transparency of the procedures, as well as the absence of fraud and data manipulation, see e.g., Bauriya et al. (2019).

The demand to provide effective tools for weighing up cryptocurrencies' trading strategies has led to a recent albeit substantial increase in statistical-econometric papers to estimate and predict specific economic variables, see e.g., Katsiampa (2017). Moreover, the key role played by cryptocurrencies as risky assets has sparked the interest of academics toward potential (in)efficiency market issues, see e.g., Le Tran and Leirvik (2020) and Brandvold et al. (2015). Finally, the research lines dedicated to the explanation of cryptocurrencies' pricing through behavioral economics is becoming increasingly popular, especially thanks to social networks, see e.g., Kim et al. (2016).

Within such a broad literature, the present paper aims at enriching the recent strand of the literature that studies technical trading rules in cryptocurrency markets, see e.g., Detzel et al. (2018), Hudson and Urquhart (2019), Vo and Yost-Bremm (2018), Cohen (2020), using statistical techniques of supervised learning for estimation and inference.

More precisely, we would like to provide innovative trading strategies on BTC. Our proposal can be seen as an appropriate compromise between gambling and building a suitable hedging portfolio. In this way, the strategy affords to mitigate the extremely speculative vocation of the former through an injection of risk aversion of the latter. The idea behind our strategy is the following. Starting from the BTC time series, we set up a predictive strategy over short time horizons. Given the number N of time buckets where it is possible to trade over such a forecasting, at the fixed initial time t_0 the trader establishes to enter into as many N *Contract for Difference* agreements (CfDs), either with short or long position, depending on the value that BTC is expected to reach with respect to a fixed threshold. The gain is achieved by exploiting the definition of CfD, viz. it is given by the difference between the BTC price and the threshold value, assessed at each time bucket. In addition, the trader can also opt for a wait-and-see strategy, which consists of selling or buying CfD only at the instant when the maximum profit is expected to be produced.

Despite not being the main focus of the present paper, BTC price prediction is not a mere byproduct. Flexible models skilful to detect hidden features driving prices are desirable to carry out predictions over time, avoiding pitfalls stemming from structural predictive models. Thanks to their capacity to process data, catching fundamental patterns within them, machine and deep learning models are suitable tools. Probing empirical BTC price demeanor, data-driven models represent prominent prototypes to reach either accuracy and reliability in predicting chaotic behavior.

Among the various machine and deep learning models existing in the literature, in this paper, we resort to the *Neural Networks* (NNs) framework. More properly, we select a *Recurrent Neural Network* (RNN) model with a *Long Short-Term Memory architecture* (LSTM, from now on), see e.g., Hochreiter and Schmidhuber (1997), in order to elaborate the observed BTC price series and project it over a designed

short term horizon. Our choice moves along the lines of Altan et al. (2019), Lahmiri and Bekiros (2019) and Lahmiri and Bekiros (2020). The latter compares disparate machine learning models to anticipate BTC price for high-frequency trading intents. Lahmiri and Bekiros (2019), firstly in the literature, proposes LSTM to foresee BTC price, bringing out RNN architecture proficiency to predict short and long fractal patterns. Finally, Altan et al. (2019) designs a innovative forecasting system based on LSTM achieving high closeness to the observed cryptocurrency prices.

Whatever the strategy undertaken by the investor, it is pivotal to assign to BTC a mathematical model capable of capturing, and possibly replicating, the evolution in time of its main characteristics and properties. The literature proposes several approaches. Looking at volatility as an indicator of the evolution of the underlying process, quite recently many authors rely on *stochastic volatility* models for BTC price dynamics, see e.g., Bohte and Rossini (2019). Moreover, justified by the empirical evidence that demonstrates the presence of large but infrequent fluctuations in the cryptocurrencies' prices, such models can be further generalized, assuming the presence of discontinuities in the dynamics, see e.g. Hou et al. (2018). Besides, the literature proposes a classic approach, based on the use of diffusive models for the price dynamics, see e.g., Bistarelli et al. (2019) and references therein. This is not a mere modeling simplification. Such a choice is justified by empirical evidence and supported by theoretical considerations. One of the techniques existing in the literature to verify whether a given phenomenon is driven by a (fractional) Brownian motion (fBM) consists in measuring the associated so-called *Hurst exponent H*. In particular, it is possible to prove that $H = 0.5$ is equivalent to saying that the corresponding fBM is a Wiener process. For further details about fBM and its generalizations, we address the reader to Bianchi and Pianese (2015) and Bianchi et al. (2015).

From an operational point of view, the literature provides several standardized algorithms to calculate the Hurst index associated with a given time series; some examples are given by the *rescaled range analysis* (R/S), the *Fourier spectral techniques* (PSD), or *wavelet variance analysis*, see e.g., Serinaldi (2010) for further details. In this paper, following the intuition exploited in Bariviera et al. (2017), we exploit the *Detrended Fluctuation Analysis* introduced in Peng et al. (1995) and Peng et al. (1994). We refer to the BTC instantaneous returns financial time series, ranging between January 1, 2019, and December 31, 2019. The empirical analysis carried out on the dataset shows that $H = 0.5$, which authorizes to assume a log-normal dynamics for the BTC prices on a short time horizon.

The novelty of our proposal resides in introducing a suitable boundary solely linked to the underlying diffusive price dynamics. To the best of our knowledge, this occurs for the first time in the literature. Such a comparison shows once again the potential of our proposal: the technical analysis performed highlights that our strategy is comparable with the others in terms of returns, but is more conservative, as it guarantees significantly lower losses.

The rest of the paper is organized as follows. In Section 2, we describe the methodology we use. In particular, we recall the financial model, as well as the main empirical results related to the data we are considering. Section 3 is devoted to the implementation of the trading strategy we present, while Sect. 4 shows numerical results that corroborate our proposal. Section 5 concludes the paper.
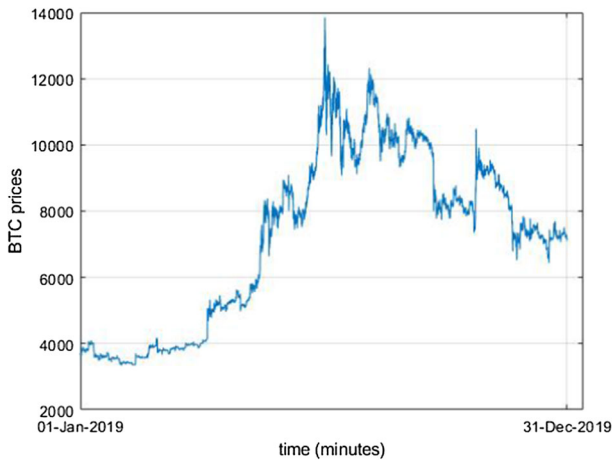
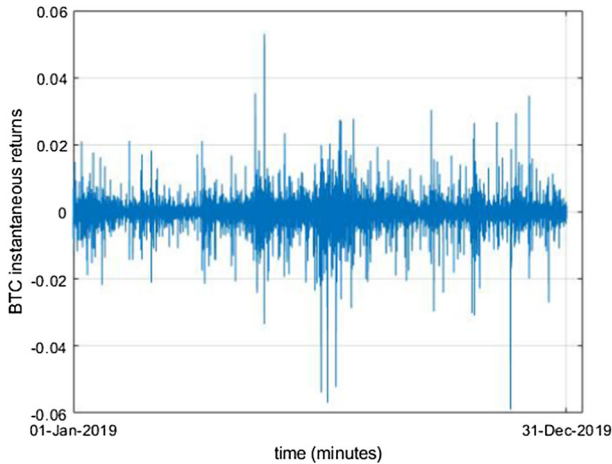**Fig. 1** BTC prices. Period: January 1, 2019–December 31, 2019

Fig. 2 BTC instantaneous returns. Period: January 1, 2019–December 31, 2019

2 BTC analysis

2.1 Dataset

In order to carry out our empirical investigations, we refer to the 2019 BTC price quotes (USD) collected from *gemini.com*. The analyzed data span from January 1, 2019, to December 31, 2019, representing the intraday 1–minute price time series, with a total of 483826 observations. In Fig. 1, we plot the BTC prices, while Fig. 2 shows the BTC returns.

For the sake of completeness, we report some statistical details related to the time series under inspection. We gather all the information in Table 1.

Table 1 Descriptive statistics of intraday BTC prices (1 minute basis)

Descriptive statistics	Values
Observations	483826
Mean	7222.06
Min	3341.6
Max	13850
Standard Deviation	2600.4
Skewness	-0.07116
Kurtosis	-1.26223
Jarque-Bera	32527

Data spans from January 1, 2019 to December 31, 2019

2.2 Empirical findings

The time series analysis described in Sect. 2.1 has a twofold relevance. On the one hand, such an investigation allows to detect the validity of the well-known *efficient market hypothesis.* On the other hand, the results might help to understand whether there exists the most suitable mathematical model to describe the evolution of the price process.

To attempt to justify both the previous points, the literature proposes the evaluation of the *Hurst exponent H* $\in (0, 1)$, see e.g., Biagini et al. (2008) and references therein for a detailed study of the topic. In other words, H means that the process, associated with the time series of which we are calculating the corresponding index, is driven by a *Fractional Brownian Motion.* Furthermore, the value assumed by H is an indicator of the presence (or absence) of long memory in the data, see e.g., Sanchez Graneroa et al. (2008).

The literature proposes several methodologies to evaluate H. In the present work, we refer to the instantaneous returns and exploit the *Detrended Fluctuation Analysis* (DFA, from now on), according to the study performed in Bariviera et al. (2017). In particular, our findings show that the Hurst exponent is $H = 0.5$ for the BTC instantaneous returns, assessed over the whole 2019. The results are obtained employing the DFA algorithm for several time windows, namely from 1 to 12 h, and we use sliding windows of 500 datapoints, as in Bariviera et al. (2017). We report such results in Figs. 3 and 4.

However, it is worth stressing that the goal of this paper is to describe a trading strategy involving BTC such that the trader can operate on a very short time horizon. To be sure that the behavior of the time series on the table remains unchanged, even when considering short time horizons, we calculate the Hurst exponent H on a time window of only one hour. The results confirm that $H = 0.5$ holds true also in this case, as it can be seen by inspection of Fig. 3a. The same behavior is exhibited when we look at 2 hours, see Fig. 3b.
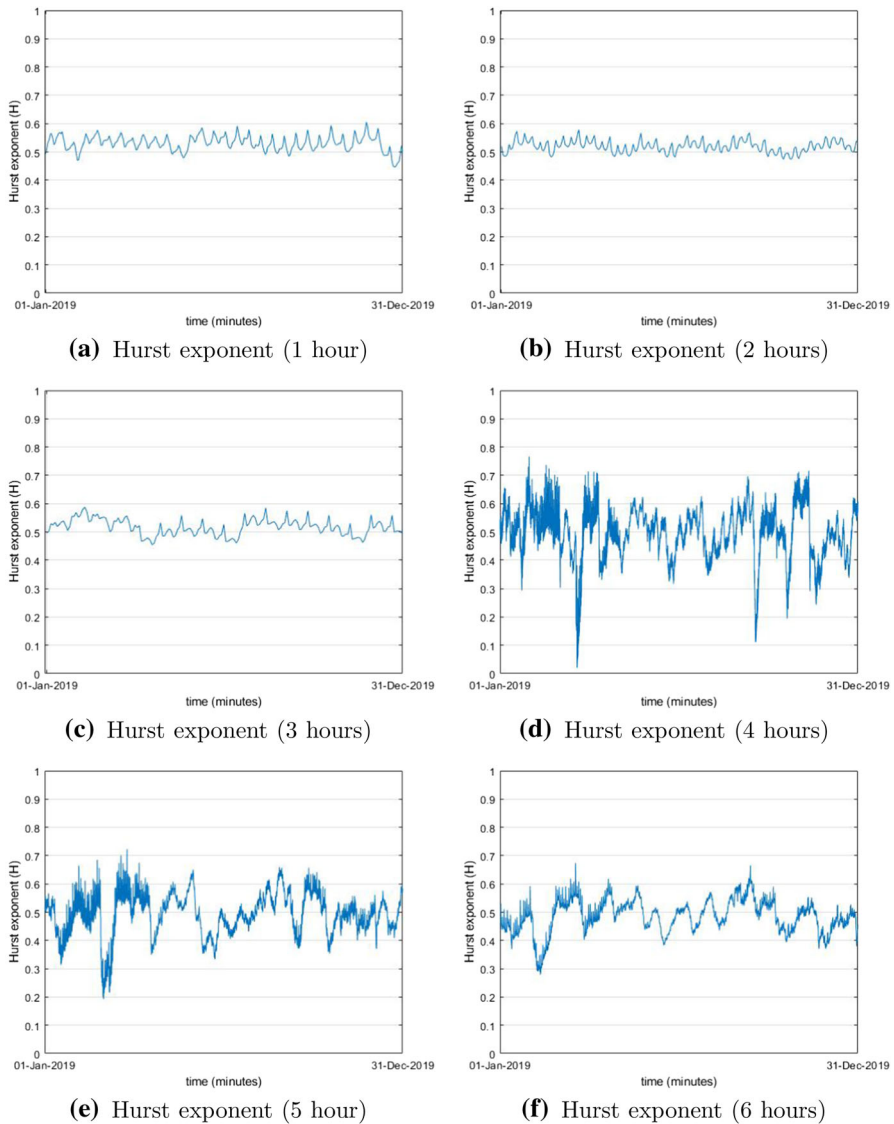
(a) Hurst exponent (1 hour)

(b) Hurst exponent (2 hours)

(c) Hurst exponent (3 hours)

(d) Hurst exponent (4 hours)

(e) Hurst exponent (5 hour)

(f) Hurst exponent (6 hours)

Fig. 3 Hurst exponent for 1 to 6 hours BTC returns, using a sliding window of 500 datapoints. Period: January 1, 2019–December 31, 2019

2.3 Theoretical framework

Once an appropriate value has been assigned to the Hurst parameter H as regards, the time series of the BTC instantaneous returns, the concluding step consists in defining a theoretical model able to characterize the BTC prices.

Let $\{S_t\}_{t \in [0,T]}$ be a stochastic process on $\left(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t \in [0,T]}, \mathbb{P}\right)$, and set $X_t = \log(S_t)$, $t \in [0, T]$. Then, the process S_t describes the BTC price, while X_t repre-

(a) Hurst exponent (7 hours)

(b) Hurst exponent (8 hours)

(c) Hurst exponent (9 hours)

(d) Hurst exponent (10 hours)

(e) Hurst exponent (11 hours)
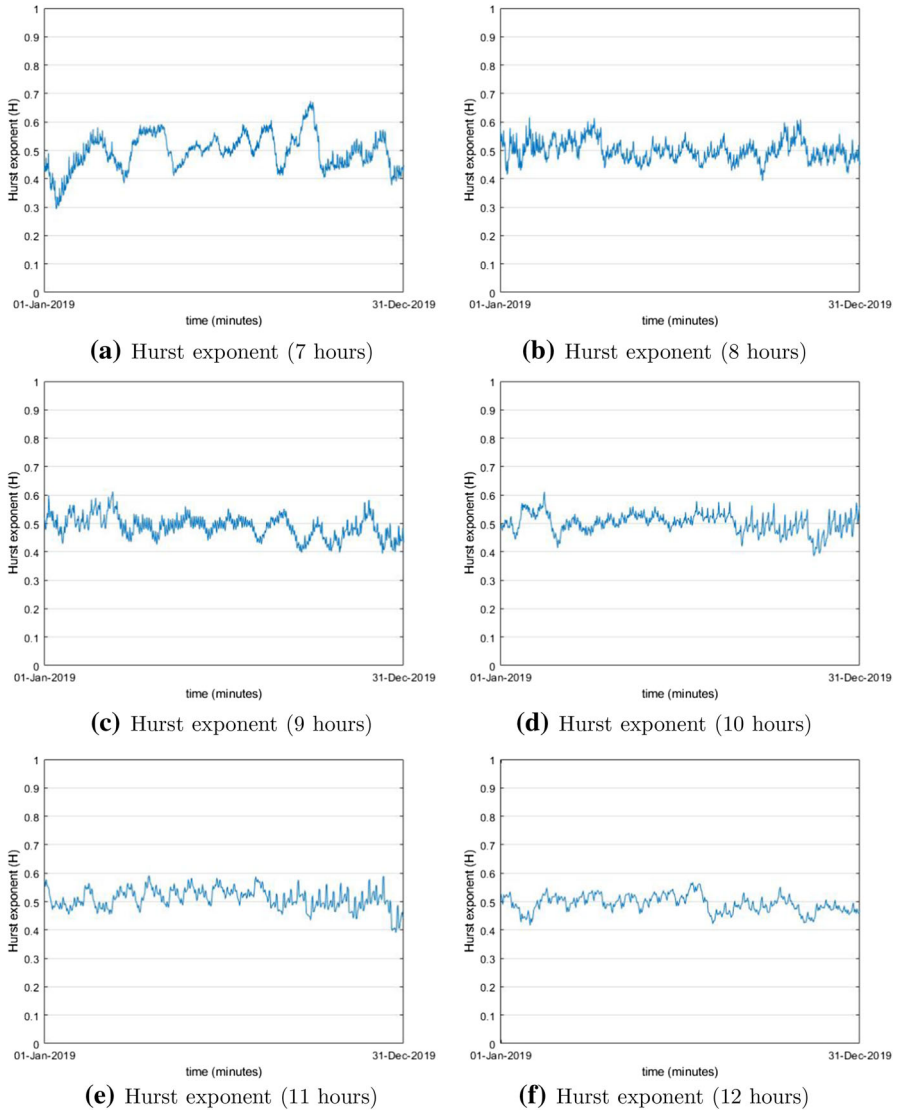
(f) Hurst exponent (12 hours)

Fig. 4 Hurst exponent for 7 to 12 hour BTC returns, using a sliding window of 500 datapoints. Period: January 1, 2019–December 31, 2019

sents the corresponding log-price process. We are interested in the time-continuous dynamics over the interval $[0, T]$, where T represents the end of a very short time horizon.

The upshot previously produced by the empirical findings, namely $H = 0.5$, reveals that the process X_t evolves according to an *Arithmetic Brownian motion* (ABM)

$$dX_t = \left(\mu - \frac{\sigma^2}{2}\right) dt + \sigma dW_t, \tag{2.1}$$

with $\mu \in \mathbb{R}^+$, $\sigma > 0$, and W_t is a Wiener process, for $t \in [0, T]$. This is justified by observing that from the empirical point of view, we work with $X_{t-u} = \ln(S_t) - \ln(S_u)$, for all $0 \le u < t \le T$, being X_{t-u} the instantaneous return associated with the time increment $t - u$. An application of Ito's Lemma ensures that the BTC price dynamics can be easily written as

$$\frac{dS_t}{S_t} = \left(\mu - \frac{\sigma^2}{2}\right) dt + \sigma dW_t, \quad t \in [0, T]. \tag{2.2}$$

Remark 1 The empirical data show that it is possible to assume that BTC prices are *locally* distributed according to a log-normal random variable. Here, *locally* means that we are considering stochastic processes in which time moves on sufficiently small intervals $[0, T]$, where the order of magnitude of T is given by hours.

Therefore, the results we obtained do not conflict with the main contributions of the literature, according to which, if we refer to a very large time span, BTC is characterized by a Hurst index $H > 0.5$. This implies that the process describing BTC prices evolves according to a Fractional Geometric Brownian motion, see e.g., Tarnopolski (2017) and references therein.

The local log-normality for the BTC price process represents one of the key points in the trading strategy we are going to describe in this paper.

3 A new trading strategy

In this section, we give survey of the main trading strategies existing in the literature and we introduce our proposal.

3.1 Technical trading strategies: an overview

The literature offers a broad range of cryptocurrencies trading strategies, see e.g., Hudson and Urquhart (2019) and Hsu et al. (2016) among others. The first family of trading rules is given by the so-called *filter rules,* see Alexander (1961). Dating back to the early 60s of the last century, these strategies act on fluctuations in the price trend, attempting to correctly identify each change in direction. A trading technique similar to filter rules is given by the *support-resistance rules.* The latter consist in creating suitable trendlines that warn to buy (resp., sell) in case of overcoming the bound from above (resp., from below). When the support/resistance levels are time-varying, the literature refers to the so called *channel breakout rules.*

A second class of trading strategies involves the *oscillator trading rules,* see e.g., Taylor and Allen (1992), where the trading signal is triggered by detecting periods of excessive buying/selling, the latter being an indicator of impending trend reversals. The indicator is given by

$$K_t = \frac{C_t - L_p}{H_p - L_p} \cdot 100 \ , \tag{3.1}$$

where C_t is the current price at time t, while H_p (resp., L_p) indicates the highest (resp., lowest) price recorded in the previous p observations. The mark is given when K_t crosses a signal line, given by a moving average of length N.

A further well-known group of trading rules is represented by the *Moving Average Convergence Divergence* (MACD, hereafter). Introduced in the 1970s, see e.g., Appel (2005), it is one of the most used momentum indicator, thanks to its ease of implementation. Roughly speaking, MACD captures bearish or bullish tendencies, analyzing the relationship between two price moving averages. More precisely, the indicator is given by

$$MACD_t = EMA_p(C_t) - EMA_q(C_t) \ , \tag{3.2}$$

where C_t is the current price at time t and $EMA_p(C_t)$, $EMA_q(C_t)$ are the *Exponential Moving Averages* over periods p and q, respectively, with $p < q$. In this case, the signal line is obtain by performing the exponential moving average of $MADC_t$ of fixed length r.

The aforementioned moving average (MA) is the key tool for another type of trading strategies. Such *Moving Average trading rules* slightly differ from the techniques previously introduced, as they directly look at the traded asset prices, without resorting to any momentum indicator, and the signal line coincides with the MA considered. The main disadvantage of such a method lies in its own asynchrony w.r.t. the true price trend, as well as the strict dependence on the length of observed data.

3.2 The proposal: the trading strategy *à la* Kim

We want to experiment a *profit-oriented* strategy at a fixed time, say t_0, in which the trader bets on BTC price changes, entering a foreordained number of financial contracts, either in short or long positions. The latter depend on the profit margin the trader would like to establish, in terms of *spread* between the predicted BTC price and a given benchmark. We agree upon letting the aforementioned starting time t_0 coincide with the last observation date in the time series.

The best-suited financial tool is given by the so called *Contract for Difference* (CfD).

A CfD is a derivative on a financial asset. It provides that two parties agree to exchange financial flow stemming from the differential between the prices of an underlying at the beginning time of the contract and at the time of its closing. Therefore, CfDs operate on the price differences, implying gain or loss according to the difference

between the purchase price and the sale price of the underlying. For the sake of simplicity, in the following, we will not consider transition and financial costs associated with CfD operations.

The touchy point is to define an appropriate benchmark. Let K be the (arranged) price agreed between the parties in the CfD, to be compared with the underlying. In t_0, we design a decision set $D := \{d_t : t \in [0, T]\}$ such that a given rule-of-thumb is satisfied, starting from $K = S_t$. In such a case, neither a long nor a short position on CfD would guarantee speculation. This form of indifference is represented by constructing a time-dependent benchmark, say $\mathcal{B}(t)$, that takes into account the market parameters (e.g., BTC price volatility level). Therefore, the buccaneering investor must define in t_0 the position to handle in order to always reach $|S_t - K|$ as margin. Typically, this translates in keeping a short position, when the downside risk is potentially unlimited. Indeed, it is straightforward to see that

$$K > S_t, \text{ or equivalently, } \max(K - S_t, 0) > 0 .$$

Vice-versa, if $K < S_t$, then

$$K - S_t < 0, \text{ or equivalently, } \max(K - S_t, 0) = 0 .$$

This means that no profit is obtained by assuming short positions, thus a change of position toward the CfD is needed. In other words, the benchmark $\mathcal{B}(t)$ comprises the time steps in which, at the same time, no trades take place and short/long position areas are defined.

Summing up, we create $\mathcal{B}(t)$ by means of a *synthetic derivative* with payoff $H_T = \max(K - S_T, 0)$ so that

– on $\mathcal{B}(t)$, we have $K = S_t$, that is, no decision is taken;
– under $\mathcal{B}(t)$, we have $K > S_t$ so d_t = short position;
– above $\mathcal{B}(t)$, we have $K < S_t$ so d_t = long position.

We observe that the BTC price evolves according to (2.2) over very short time horizons, as already stressed in Sect. 2.3. Hence, we can exploit the results given in Kim (1990), provided that the risk-neutral probability measure $\mathbb{Q} \sim \mathbb{P}$ is defined. The boundary *à la* Kim $\mathcal{B}(\tau)$, as a function of the time to expiration $\tau = T - t$ and in the absence of continuous dividend yields δ, coincides with the (unique) solution to the following weakly singular Volterra integral equation

$$
\begin{aligned}
K - \mathcal{B}(\tau) = {} & K e^{-r\tau} \Phi \left(-\frac{\log\left(\frac{\mathcal{B}(\tau)}{K}\right) + (r - \frac{\sigma^2}{2})\tau}{\sigma\sqrt{\tau}} \right) \\
& - \mathcal{B}(\tau) e^{-\delta\tau} \Phi \left(-\frac{\log\left(\frac{\mathcal{B}(\tau)}{K}\right) + (r + \frac{\sigma^2}{2})\tau}{\sigma\sqrt{\tau}} \right) \\
& + K r \int_0^\tau e^{-r(\tau-s)} \Phi \left(-\frac{\log\left(\frac{\mathcal{B}(\tau)}{\mathcal{B}(s)}\right) + (r - \frac{\sigma^2}{2})(\tau - s)}{\sigma\sqrt{\tau - s}} \right) ds , \quad (3.3)
\end{aligned}
$$

where Φ is the standard cumulative normal distribution function. Moreover, an application of (Kim 1990, Proposition 2) shows that our benchmark $\mathcal{B}(\tau)$ is a continuously differentiable function on $(0, T]$ and $\lim_{\tau \to 0} \mathcal{B}(\tau) = K$.

We summarize the main steps to be done in t_0 to obtain our trading strategy. Recall that t_0 represents the last observation time in the BTC time series. We assume that t_0 coincides with the starting point of our strategy.

Step 1. Given the time interval $[0, T]$, set the partition π such that

$$0 = t_0 < t_1 < \ldots < t_{N-1} < t_N = T \ .$$

Step 2. Determine the future trajectory $\{V_t\}_{t \in \pi}$.

Step 3. Construct a synthetic *American-style* derivative with strike price K, maturity T^* and payoff $H_{T^*} = \max(K - V_{T^*}, 0)$. More precisely, T^* is chosen in such a way that it coincides with the end of the trading period, i.e., $T^* = T$, while the strike price is such that $K = V_{t_1}$, i.e., it coincides with the predicted price of the BTC assessed in the first forecasting time step.

Step 4. Solve the integral Eq. (3.3) by means of the trapezoidal rule, to determine the optimal boundary $\mathcal{B}(\tau)$. Recall that here $\tau = T - t$, with $t \in \pi$. Hence, to be able to make the values of V and $\mathcal{B}$ comparable, we must flip the latter. The model parameters are estimated by exploiting the maximum likelihood method suggested in Brigo et al. (2007).

Step 5. For all $t_i \in \pi$, define

$$Y_i := B_{t_i} - V_{t_i} \begin{cases} > 0, & \text{implying that a short position is requested,} \\ = 0, & \text{implying that no trades are done} \\ < 0, & \text{implying that a long position is requested.} \end{cases}$$

Consequently, we set h (resp. k, j) the amount of times in which Y_i is greater than (resp., equal to or smaller than) zero. Then, the strategy is composed of h long CfDs and j short CfDs.

Step 6. (Optional) Evaluate the overall profit

$$G := \sum_{i=0}^{h} (B_{t_i} - V_{t_i}) + \sum_{i=0}^{j} (V_{t_i} - B_{t_i}) \ .$$

Step 7. (Optional) Determine the time step $t' \in \pi$ (resp., $t'' \in \pi$) where the maximum gain from short position (resp., long position) is obtained.

4 Numerical experiments

To proceed with our proposal, we must perform the algorithm provided in Sect. 3.2.

4.1 BTC price forecasting

Once the time horizon has been partitioned, the first stumbling block is to predict the BTC price.

We exploit the LSTM network endorsing an autoregressive approach on 1-minute basis. We refer the reader to Nigri et al. (2020) for more technical and theoretical details related to the LSTM network.

Therefore, we can properly formalize each realization, over time, of the future BTC price as follows:

$$\bar{S}_t = f_{LSTM}\left(\bar{S}_{t-1}, \boldsymbol{\Theta}\right) + \varepsilon_t, \tag{4.1}$$

with f_{LSTM} the NN function, $\boldsymbol{\Theta}$ the set of NN parameters and ε_t a zero mean error component with variance σ_ε^2. The future BTC price trajectory, $(V_t)_{t\in\pi}$, is given by the following point prediction equation:

$$V_t = \mathbb{E}^{\mathbb{P}}\left(\bar{S}_t \middle| \bar{S}_{t-1}\right) = f_{LSTM}\left(\bar{S}_{t-1}, \hat{\boldsymbol{\Theta}}\right). \tag{4.2}$$

Starting from the original BTC price dataset mentioned in Sect. 2.1, we proceed to calibrate the LSTM network selecting three different closing price samples. More in details, we consider intraday 1-minute price for windows of 180, 360 and 720 datapoints, to train and test the LSTM model. Training and testing sets are generated according to the splitting rule 80%-20%. Moreover, to define the composition of the LSTM architecture, a fine tuning process is implemented by adopting a grid search technique. Because of that, a limited, discrete parametric space is established *a priori,* whose possible values are arbitrarily chosen, acting as LSTM hyperparameters. Fixing a combination of hyperparameters in the parametric space, the training procedure begins by minimizing the mean squared error as loss function. We elect the optimal NN architecture the one identified by the hyperparameters combination returning the minimum error on the testing set.

The analysis is implemented using the R software (version 3.6.3) exploiting the Keras package. In Table 2, the LSTM calibration results are summarized.

The results in Table 2 can be integrated into the preexisting literature: indeed, on top of Lahmiri and Bekiros (2019), we show that the LSTM is an accurate predictor also in the absence of chaoticity. Moreover, although the LSTM is typically employed in managing big data, our RMSE and MAE suggest an efficient envisage capability also for smaller samples. This further ensures a significant shrinking of the computational burden.

4.2 Performance analysis

To establish the accuracy of the new trading strategy, we compare our results with those obtained by applying other trading rules already known in the literature. Among the possible methodologies introduced in Sect. 3.1, we choose three competitors, namely

Table 2 For each sample size considered, we report the 3D-tensor shape for training data, the hyperparameters values stemming from the fine tuning process and accuracy metrics values

Key information	180 minutes	360 minutes	720 minutes
3D-tensor training input shape	(144,1,1)	(288,1,1)	(576,1,1)
Feed-Forward activation function	Rectified Linear Unit	Rectified Linear Unit	Rectified Linear Unit
Recurrent activation function	Hyperbolic Tangent	Hyperbolic Tangent	Hyperbolic Tangent
Dropout rate	0.2	0.2	0
Loss Function	Mean Squared Error	Mean Squared Error	Mean Squared Error
Optimizer	Adam	Adam	Adam
No. hidden layer	1	1	1
No. dense layer	1	1	1
No. (LSTM) neurons	41	90	108
No. epochs	10	5	23
RMSE	3,755	5,324	5,838
MAE	2,785	4,297	4,690

the MACD, the Stochastic Oscillator and the Moving Average with different time windows.

The comparison has been performed by using proper indicators, capable to assess the risk-return profile of each strategy involved. More properly, we begin by evaluating the *Sharpe ratio* (SHR). To further distinguish among trading strategies with similar behaviors in terms of average returns, we check the excess return against a minimum acceptable (risk-free) rate, thanks to the *Sortino ratio* (SOR). The risk measure involved is the *Downside risk* (DSR), ensuring to look at the distribution left tail. It is worth recalling that a greater SOR means that the variability is concentrated above the fixed threshold; vice versa, a smaller SOR means that the variability is concentrated below the fixed threshold.

It is also important to measure the strategy's historical loss. This is assessed by the *Maximum Drawdown* (MDD), i.e., the largest loss the investors might face when they buy at highest level and sell at lowest level.

Finally, a meaningful parameter is given by the so called *Win ratio* (WR), serving as a measure of investments' profitability. WR is defined as a ratio, comparing the trading periods with positive gains and the overall trading times. A greater WR represents a better accuracy in the predicted trading strategy.

4.2.1 Trading strategy *à la* Kim vs. MA-based trading strategy

We would like to stress once again that our proposal is based on the construction of a specific threshold which ensures to evaluate gains/losses in terms of CfDs. On the other hand, it is equally undeniable that the moving average represents, by its very nature, a comparison level for BTC price. Hence, the MA strategy embodies a feasible competitor, whatever the size of the time window taken into account.

The comparison between our proposal and MA is shown in Table 3. Scrutinizing the results obtained, we find out that the uppermost Sharpe ratio is provided by MA(10) for 60-minute and 90-minute predictions. Consequently, the average return of the entire strategy results to be the highest. For the 120-minute case, the first-past-the-post-strategy is MA(120). Such excellent upshot basically depends on the intrinsic nature of such a strategy; in fact, for MA rules, the threshold closely follows the prediction evolution.

However, the latter also reveals some notable drawbacks. First, too few observations for the moving average are meager to properly identify the flawless trading times. This clearly comes to light by looking at MA(5). In this perspective, our proposal soundly differs from the aforementioned investment rule, as our barrier is independent of the BTC price paths. Even though this could imply lower profits, the maximum drawdown shows that our proposal always ensures the lowest loss, highlighting its *safeguarding* role. Furthermore, it is worth noting that the risk measures are not computable for each MA-based strategy, since the barrier is constructed in such a way that the zenith never takes place after the nadir.

Finally, combining the ability to limit losses (given by MDD) with the penchant for obtaining a considerable percentage of positive profits (measured through WR), we can conclude that the strategy *à la* Kim is successful and promising.

Table 3 Performance analysis for the Kim-based strategy (our proposal) *vs.* the MA(*n*) rule with *n* = 5, 10, 15, *N*, being *N* = 60, 90, 120 the length of the forecasting

	SHR	SOR	WR	MDD	No. Buys	No. Sells	Av. returns (%)
Panel A: 60 minutes forecasting							
Kim	0.0169	0.0232	**0.9167**	**−0.1540**	55	5	1.2677
MA(5)	−0.1235	−0.1316	0.5667	–	34	26	−81.3819
MA(10)	**0.1085**	0.3460	0.6000	–	36	24	**81.6102**
MA(15)	−0.1927	−0.2041	0.6167	–	37	23	−39.5271
MA(60)	0.0203	0.0328	0.5333	−0.5211	32	28	2.9924
Panel B: 90 minutes forecasting							
Kim	−0.0164	−0.0215	**0.9778**	**−0.0950**	88	2	−2.6252
MA(5)	−0.0538	−0.0722	0.5333	–	48	42	−49.4956
MA(10)	**0.1447**	0.6855	0.6111	–	55	35	**137.9892**
MA(15)	−0.2040	−0.2165	0.6111	–	55	35	−62.7339
MA(90)	−0.0731	−0.0850	0.6889	−0.5229	62	28	−5.9564
Panel C: 120 minutes forecasting							
Kim	0.0896	0.1623	**0.9917**	**−0.0271**	119	1	4.1879
MA(5)	−0.0332	−0.0457	0.5750	−0.4328	69	51	−27.3983
MA(10)	0.0868	0.2553	0.6583	−0.3898	79	41	**74.9713**
MA(15)	−0.1207	−0.1222	0.6667	−0.3157	80	40	−148.9885
MA(120)	**0.1285**	0.2348	0.7583	−0.2582	91	29	8.5127

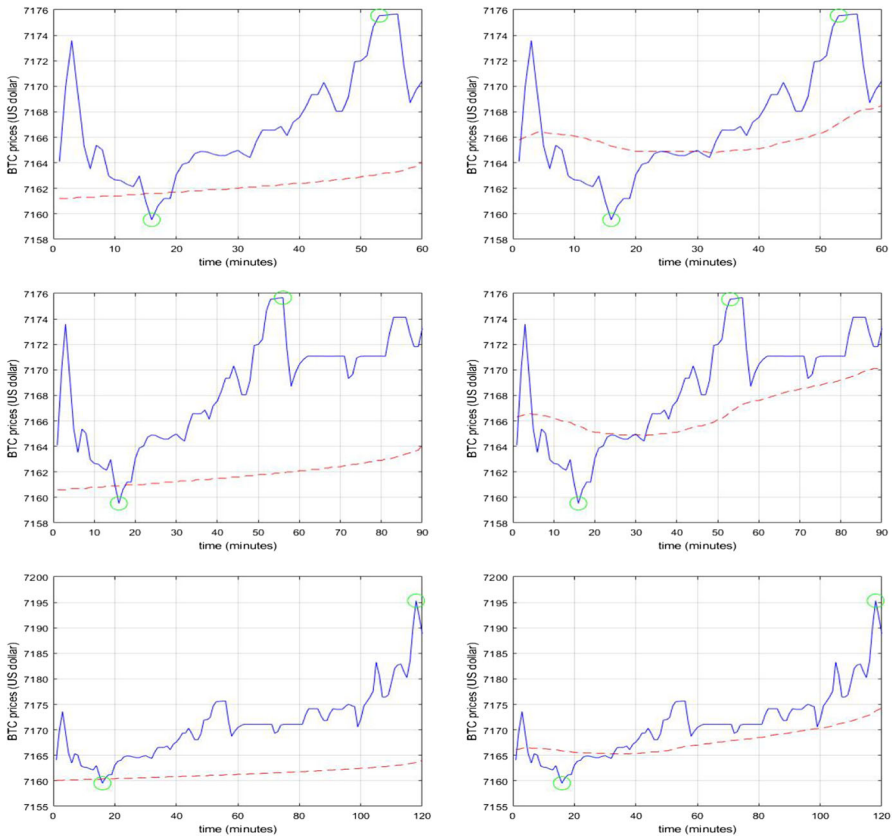The best performances are highlighted in bold

Fig. 5 Trading strategy over different time horizons. The forecasting starting time is December 31, 2019–23:59. The solid line represents the LSTM forecasting for BTC price, the dotted line is optimal boundary. The two circles indicate the maximum profit realized by the investor, both in long and short position

In Figure 5, we depict our trading strategy *à la* Kim, compared to the MA-based trading strategy. The solid line represents the forecast for the BTC price over a different time intervals, measured minute by minute. The forecasting was obtained by implementing the LSTM method introduced above. The dotted line represents the benchmark, i.e., the optimal boundary related to the synthetic derivative evaluated *à la* Kim (left charts) and the moving average (right charts). The two circles indicate the *optimal* trading times t' and t'', with $t' < t''$, if the investor would like to opt for a wait-and-see strategy. We further note that t' is the optimal time for the long CfD position, while t'' represents the optimal time for the CfD short position.

4.2.2 Trading strategy *à la* Kim vs. MACD and Stochastic Oscillator

We recall that MACD and stochastic oscillator rules are defined in terms of suitable parameters. The latter can be explicitly evaluated, thanks to (3.2) and (3.1), respectively. This makes the aforementioned strategies particularly all-around. Hence, to

Table 4 Performance analysis Kim strategy vs. standard trading strategies

	SHR	SOR	WR	MDD	No. Buys	No. Sells	Av. returns (%)
Panel A: 60 minutes forecasting							
Kim	**0.0169**	0.0232	**0.9167**	**−0.1540**	55	5	**1.2677**
MACD	−0.0887	−0.1621	0.3333	−0.5412	1	2	−0.0091
St. os.	0.0097	0.0120	0.6842	–	13	6	$4.2214 \cdot 10^{-4}$
Panel B: 90 minutes forecasting							
Kim	−0.0164	−0.0215	**0.9778**	**−0.0950**	88	2	−2.6252
MACD	−0.0670	−0.1122	0.4000	−0.5412	2	3	−0.0049
St.Os.	**0.0513**	0.0658	0.7600	–	19	6	**0.0019**
Panel C: 120 minutes forecasting							
Kim	0.0896	0.1623	**0.9917**	**−0.0271**	119	1	**4.1879**
MACD	**0.8197**	6.7854	0.8333	−0.1062	5	1	0.0575
St.Os.	0.2215	0.3651	0.7879	−0.6949	26	7	0.0094

The best performances are highlighted in bold

complete our investigation, we exhibit the performance analysis for MACD, Stochastic Oscillator and our strategy: the comparison is illustrated in Table 4.

Looking at the parameters involved, we can claim that our proposal comes out on top, both in terms of risk and return, when we consider an hourly forecasting time window. When the time horizon increases the performances of all strategies slightly worsens. More precisely, for the 90-minute prediction, our proposal and MACD provide negative returns; any risk-seeking investor would be geared toward the stochastic oscillator rule. As the investors' risk aversion increases, the role played by MDD becomes prominent. For the longest forecast, namely 120 minutes, although our strategy is dominated by the other two if we refer to the Sharpe ratio only, the results are certified to be outstanding when considering its ability to contain losses.

The comparison between our strategy *à la* Kim and MACD or stochastic oscillator captures additional value when we examine our proposal *per se:* it is well-known that BTC represents a highly volatile asset. Therefore, wise investors are led not to directly invest in BTC, in order not to incur potentially significant losses of their wealth. This can be inferred by observing the risk indicator taken into consideration, i.e., MDD, in Table 4. The curtailment of these values, emerging whenever the investor prefers our proposal, is justified precisely in terms of CfDs: such a form of derivative on BTC, which is an integral part of the proposal introduced in this work, enhances the strategy's performances and makes it attractive to a wide range of potential investors.

5 Conclusions

In this article, we exhibit an original profit-oriented trading strategy on BTC for risk-seeking investors.

The idea is simple, but compelling. We can set up the strategy, by taking into account a given number of suitable financial instruments (the so-called contracts for difference) that provide profit in terms of the spread between the underlying value and the optimal frontier of a synthetic American-style derivative.

One of the key points of this work is the possibility of evaluating the BTC price through a geometric Brownian motion over very short time horizons. This is empirically justified by the observation that, for such time frames, the log-returns show a Hurst index equal to $H = 0.5$.

The results presented here, stemming from the comparison between the NNs BTC price prediction and a suitable model-based investment boundary, represent a first, albeit significant, attempt. The technical analysis pursued on the proposed Kim-barrier strategy, in comparison with other trading rules widely used by insiders, provides encouraging results about the appropriateness of our proposal. The latter can be legitimately deemed as a viable alternative for investors looking for a profitable-but-protective trading blueprint.

One further development, which is already subject of our ongoing research, is the extension of such a type of trading strategy when the underlying evolves according to more realistic models, such as the fractional geometric Brownian motion or stochastic volatility models with jumps.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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